Natural Language Processing Methods for Air Traffic Management Text and Speech Data

Stephen Clarke, Jacqueline Almache, Swetha Rajkumar, Shyam Nuggehalli and Jordan Majoros

Mentors: Krishna Kalyanam, Mick Welfare and Raj Pai

Code: A

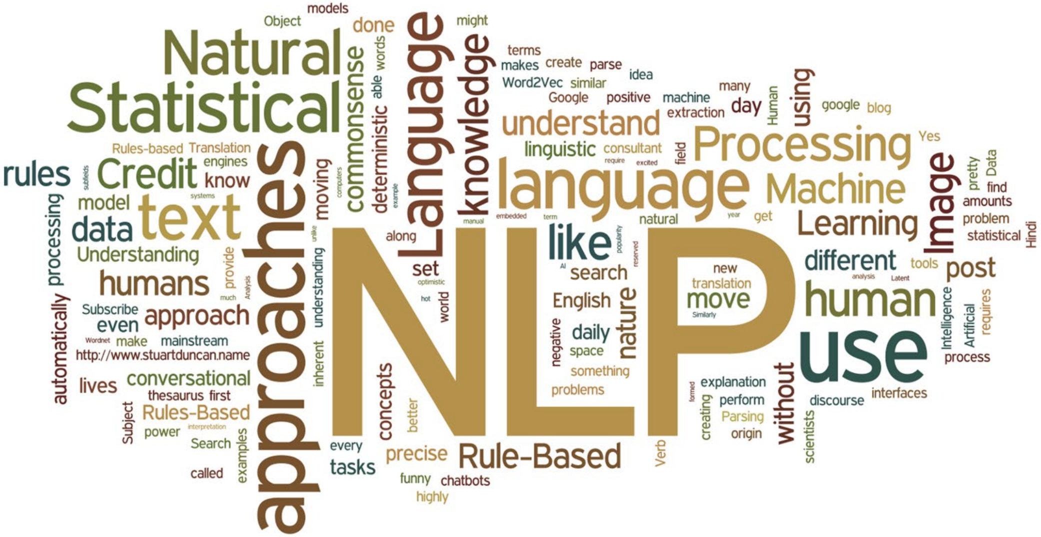
Fall 2021

Agenda

- Introduction
- Letters of Agreement (LoA)
- Speech
- Questions

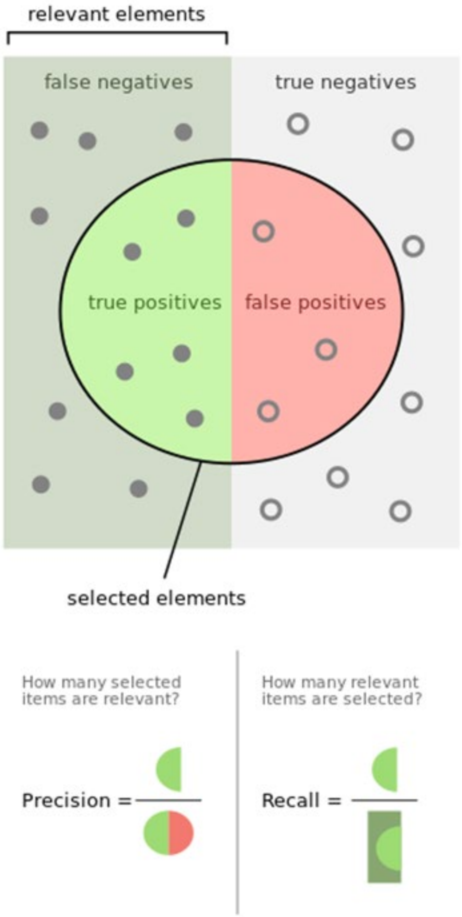
Background: Natural Language Processing (NLP)

- How can we represent words as numbers?
  - Word embeddings
- Research Applications
  - Information Extraction
  - Pattern Finding
  - Topic Modelling
- Deep Language Models
  - Bidirectional Encoder Representations from Transformers (BERT)



Metrics for NLP

- $Precision = \frac{TP}{TP+FP}$
- $Recall = \frac{TP}{TP+FN}$
- $F1 = \frac{2 * Precision * Recall}{Precision + Recall}$
- $WER = \frac{Substitutions + Deletions + Insertions}{Total\ Words}$



Letters of Agreement

Letters of Agreement Overview

- Data
- Understanding constraints in LoAs
  - Define a constraint
  - Unsupervised exploration
- Entity recognition
  - Dictionary Replacement
  - Pattern Matching
- Identifying and extracting constraints

Letters of Agreement

- **Definition: Letters of Agreement (LoAs) are longer documents outlining the procedures and restrictions for aircraft operations**

- Our dataset contains a statistically significant sample of LoAs from different Air Route Traffic Control Centers (ARTCC).

(Name) Air Route Traffic Control Center and (Name) Air Division

LETTER OF AGREEMENT

EFFECTIVE: _______

SUBJECT: Interfacility Coordination for the Control of Aerospace Defense Command Interceptor Aircraft.

1. **PURPOSE:** (List responsibility and describe necessary coordination.)

2. **CANCELLATION:** (As required.)

3. **SCOPE:** (Specify area, names, and types of facilities involved.)

4. **RESPONSIBILITIES:** (Specify.)

5. **PROCEDURES:**
   a) ATC Assigned Airspace.
   b) Transfer of Control.
   c) Departure.
   d) En Route.
   e) Arrivals.
   f) General.

6. **ATTACHMENTS:** (List, as required, items such as chart of ATC-assigned airspace areas, common reference/handoff points, etc.)

____

Air Traffic Manager, (Name) ARTCC

____

Commander, (Name) Air Division

____

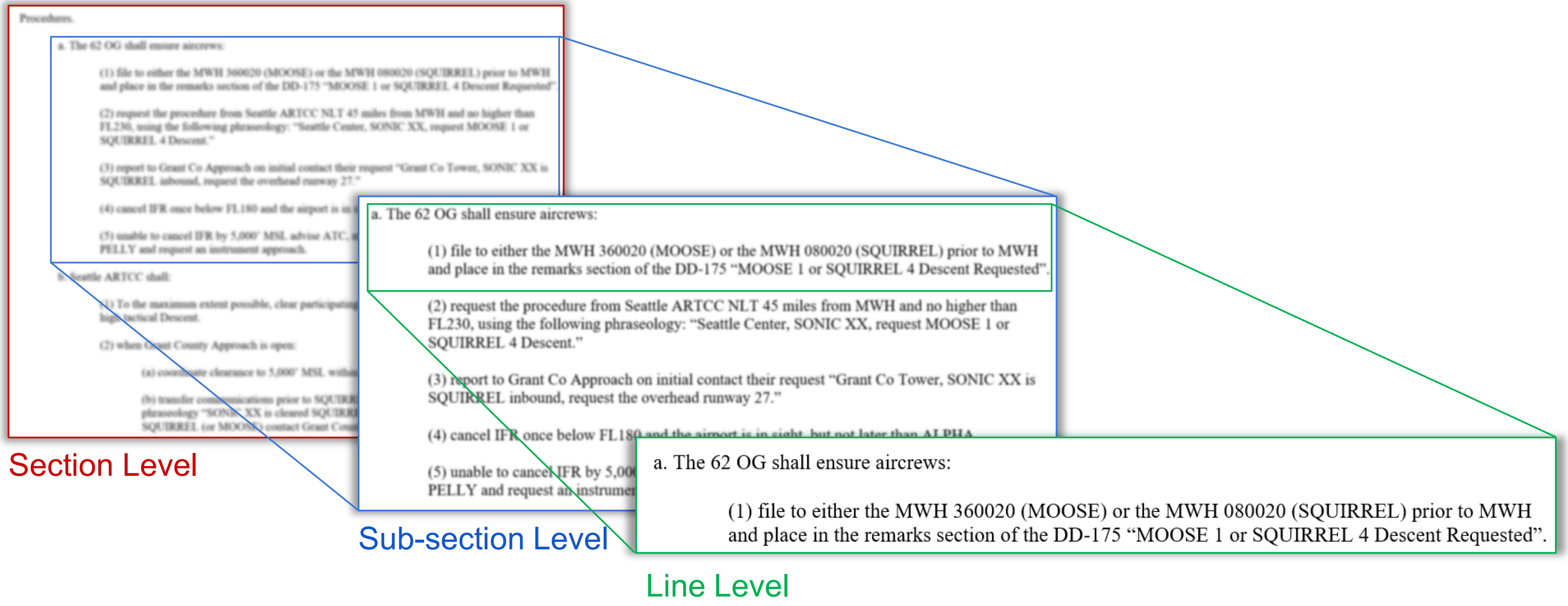
(Title of other appropriate authority)

LoA Constraints

Question: “What is the smallest unit of information within an LoA?”

- Procedure (or section level)
  - Too large. Could contain multiple units of information.
- Subsection Level
  - Ambiguous, since the same information may be contained in the sub-sub-section of one LoA and sub-sub-sub-section of another.
- **Line Level - Final Choice**
  - Consistent across LoAs and good size.
  - Must assume independence from other line-level information.

LoA Constraint Example



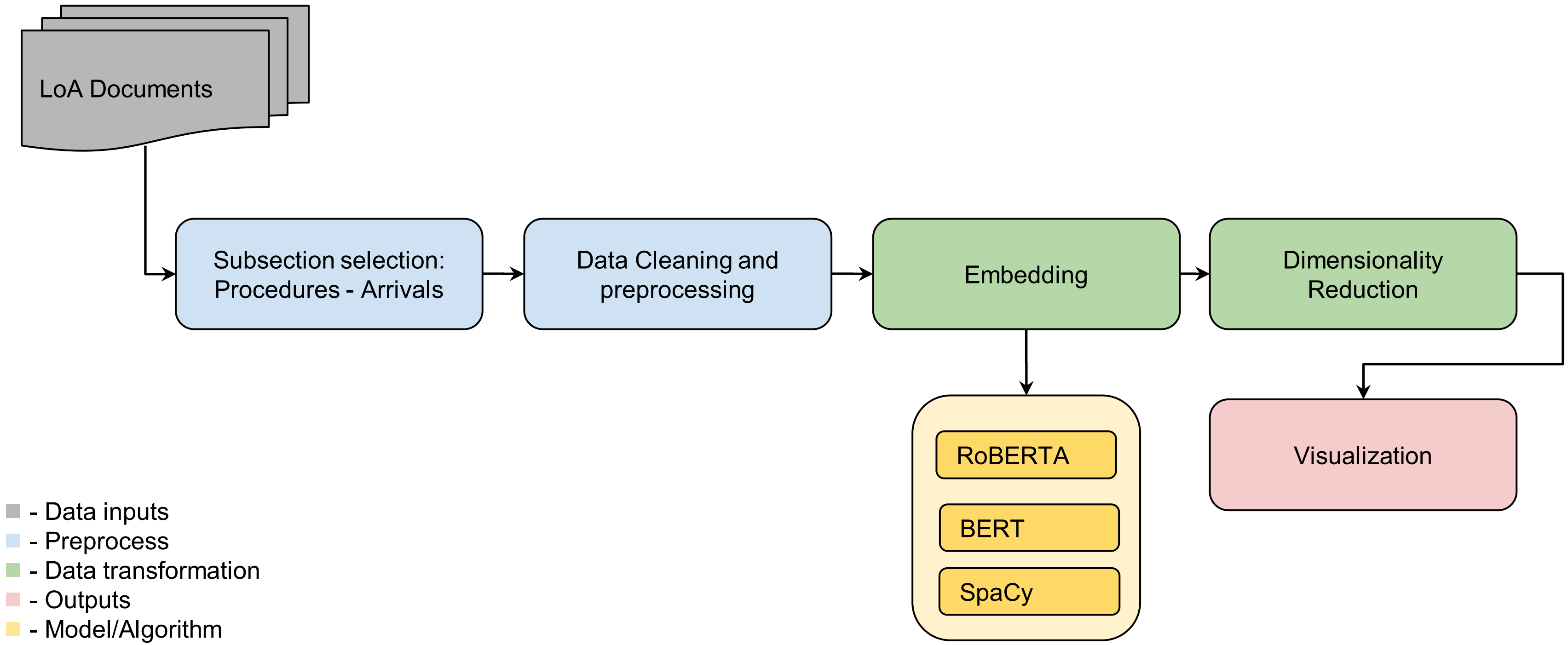
LoA Constraints (cont.)

Number of constraints based on chosen constraint unit

Data Unit	Total Occurrences
Section Level	1072
Subsection Level	5643
Line Level	19979

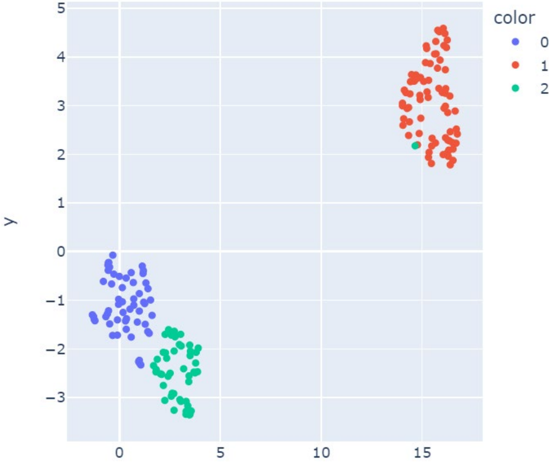
- Note: Contains numbers from 1419 ARTCC LoAs.

Unsupervised Analysis: Embedding and Clustering



Unsupervised Analysis Using HDBSCAN

- Robustly Optimized BERT (RoBERTa) Embedding Vectors, dimensionality reduction using UMAP (Uniform Manifold Approximation and Projection for Dimension Reduction), and HDBSCAN for clustering.
- Word cloud to visualize the most common words on each cluster.



Creating a Labeled Dataset

- Dictionary replacement
- Pattern matching
- IOB Formatting
  - **I**nside - Inside an entity
  - **O**utside - All words that are unrelated to an entity
  - **B**eginning - Beginning of an entity

Pilots	must	maintain	12,000	feet	MSL
O	O	O	B-Altitude	I - Altitude	I - Altitude

Labelling using Dictionaries

- Within LoAs, a lot of entities referenced are names of facilities such as airports, Terminal Radar Approach Control (TRACONs), and other facilities.
- These common names are well known, and vital information to a constraint.
- Therefore, we can use dictionaries of these words to label entities.

Word	Name	State
A11	Anchorage TRACON	AK
A80	Atlanta TRACON	GA
A90	Boston TRACON	NH
C90	Chicago TRACON	IL
D01	Denver TRACON	CO
D10	Dallas-Fort Worth TRACON	TX
D21	Detroit TRACON	MI
F11	Central Florida TRACON	FL
I90	Houston TRACON	TX
L30	Las Vegas TRACON	NV
M03	Memphis TRACON	TN
M98	Minneapolis TRACON	MN
N90	New York TRACON	NY
NCT	Northern California TRACON	CA
P31	Pensacola TRACON	FL
P50	Phoenix TRACON	AZ
P80	Portland TRACON	OR
PCT	Potomac TRACON	VA
R90	Omaha TRACON	NE
S46	Seattle TRACON	WA
S56	Salt Lake City TRACON	UT
SCT	Southern California TRACON	CA
T75	St. Louis TRACON	MO
U90	Tucson TRACON	AZ
Y90	Yankee TRACON	CT

ZNY	must	consult	with	N90	and	PHL	TRACON
B-ARTCC	O	O	O	B-TRACON	O	B-TRACON	I-TRACON

Labeling Using Pattern Matching

- Certain entity labels follow specific language patterns that can be identified and used for labelling.
  - For example, altitudes follow very common patterns.

12,000 feet MSL

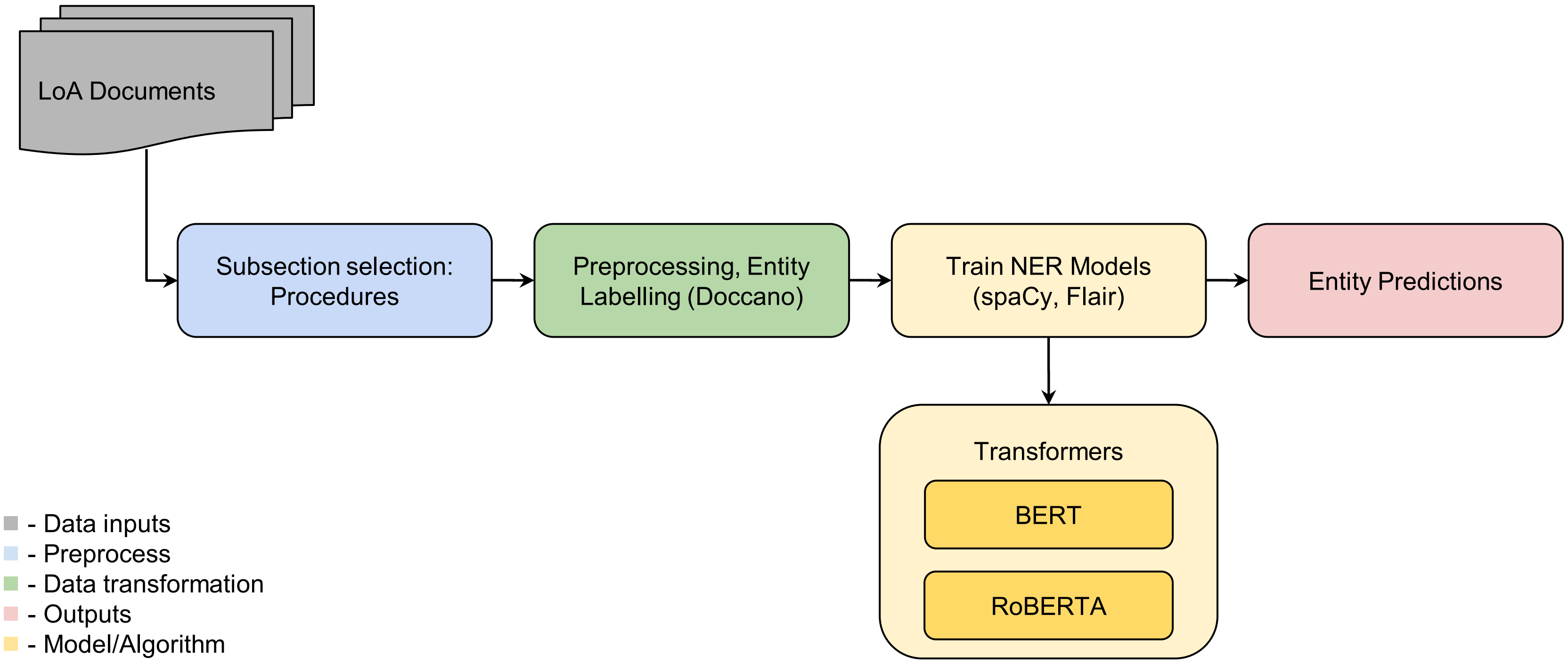
Number potentially separated by commas

Unit, typically feet, ft, or even “ symbol

MSL - mean sea level. Could also be AGL - above ground level

- Some other labels that follow common patterns are speeds, phone numbers and latitude/longitude positions

Future Work: Named Entity Recognition Pipeline

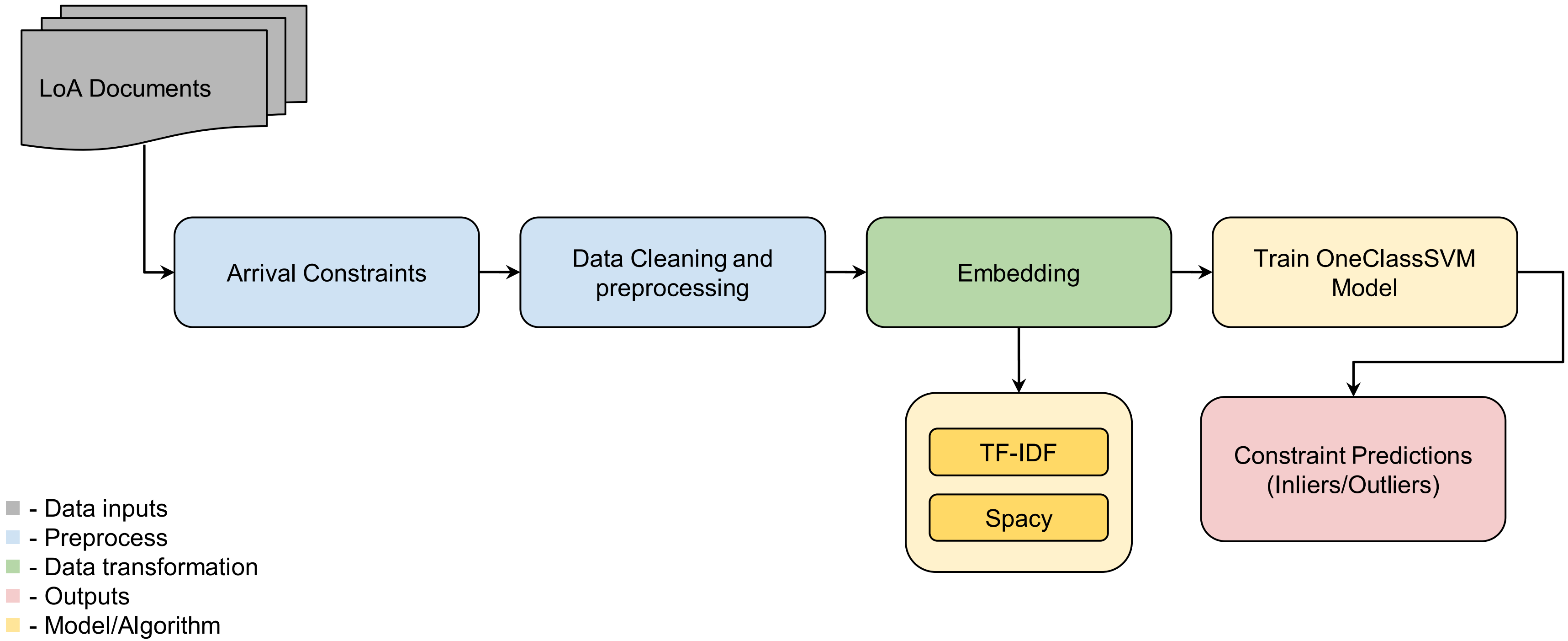


- Data inputs
- Preprocess
- Data transformation
- Outputs
- Model/Algorithm

Constraint Identification

- Goal: Give context to extracted entities, making relationships between actors and actions.
  - Example
    - 1. [AIRCRAFT] landing at [AERODROME] must use [RULE] when leaving [AIRSPACE] of [ARTCC]
    - 2. [AIRCRAFT] leaving [AIRSPACE] must be at [ALTITUDE] when leaving [AIRSPACE] of [ARTCC]
- How to extract these patterns
  - Following word-for-word or entity-for-entity
  - Machine learning: One Class Support Vector Machine (SVM)
  - Machine learning: finding similar word embeddings
- Need to think about how these patterns fit into current exchange models

SVM Workflow Visual



Constraint Identification Example

Arrival Constraint: Radar. Arrivals; Center shall clear arrivals to the Greensboro terminal area as follows: Prop arrivals operating at 10,000 feet or below shall cross the Tower boundary at an altitude appropriate for direction of flight and may be cleared direct to the destination airport.

OneClassSVM Classification: Arrival

SVM Score: 0.928

Exchange Models

- When identifying constraints, it is important to understand how these will be distributed within the National Airspace System (NAS). Currently, there are three major information formats used.
- Aeronautical Information eXchange Model (AIXM)
    - “Enables the provision in digital format of the aeronautical information that is in the scope of Aeronautical Information Services” - aixm.aero
- Flight Information eXchange Model (FIXM)
    - Global exchange standard for capturing flight and flow information
- FLow information eXchange Model (FLXM)
    - FLXM supports the ATFM (Flow) information domain. Created as a solution to the gaps in flow information from FIXM

Future Work

- Possibility of using Named Entity Recognition (machine learning)
- Reporting labelling accuracy/metrics
- Patterned constraints must be defined
- Start defining LoAs within exchange model

Letters of Agreement

Questions?

Speech Summarization

Overview

- Data
- Methodology
- Supervised Speech Summarization
- Future Work

ATCSCC Meeting Recordings

- Air Traffic Control System Command Center (ATCSCC) meetings, last on average around 10-15 minutes
- Airports, data centers, and stakeholders discuss flight operations and airspace activities
- The meetings are held around every two hours, or when needed, starting at 9am EST

Operations Plan Advisories

- ATCSCC Operations Plan Advisory
- Discussions on Traffic Management Initiatives (TMI) during unexpected events/operations
- **Goal**: Use AI/ML to generate summaries
- **Purpose**: Make generating summaries easier

ATCSCC ADVZY 157 DCC 08/14/2018 OPERATIONS PLAN

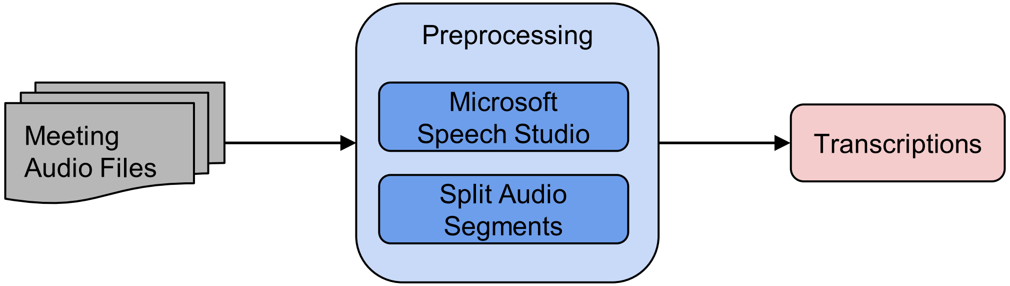
```
EVENT TIME: 14/2000 - AND LATER
OPERATIONAL GOALS FOR 8/14/18
- MANAGE EWR/LGA/JFK/PHL/TEB AIRPORT OPERATIONS TO KEEP DEPARTURE
DELAYS TO LESS THAN 75 MINUTES AND AIRBORNE HOLDING TO LESS THAN 30
MINUTES.
- MANAGE DCA/IAD/BWI AIRPORT OPERATIONS TO KEEP DEPARTURE DELAYS TO LESS
THAN 75 MINUTES AND AIRBORNE HOLDING TO LESS THAN 30 MINUTES.

SFO PROGRAM TO REVISE COMING OUT OF GROUND STOP EXPECT CONFERENCE SHORTLY.
WEATHER CONDITIONS AT EWR DETERIORATING. LGA PROGRAM SET AT REDUCED
AIRBORNE RATE TO PROTECT SURFACE DUE TO DEPARTURE BACKLOGS FROM LACK OF
DEPARTURE ROUTES.

TERMINAL ACTIVE:
UNTIL 2159      -SFO GROUND DELAY PROGRAM
UNTIL 0059      -PHL GROUND DELAY PROGRAM
UNTIL 0459      -BOS GROUND DELAY PROGRAM
UNTIL 0559      -LGA GROUND DELAY PROGRAM
UNTIL 0759      -EWR GROUND DELAY PROGRAM
UNTIL 0459      -JFK GROUND DELAY PROGRAM
```

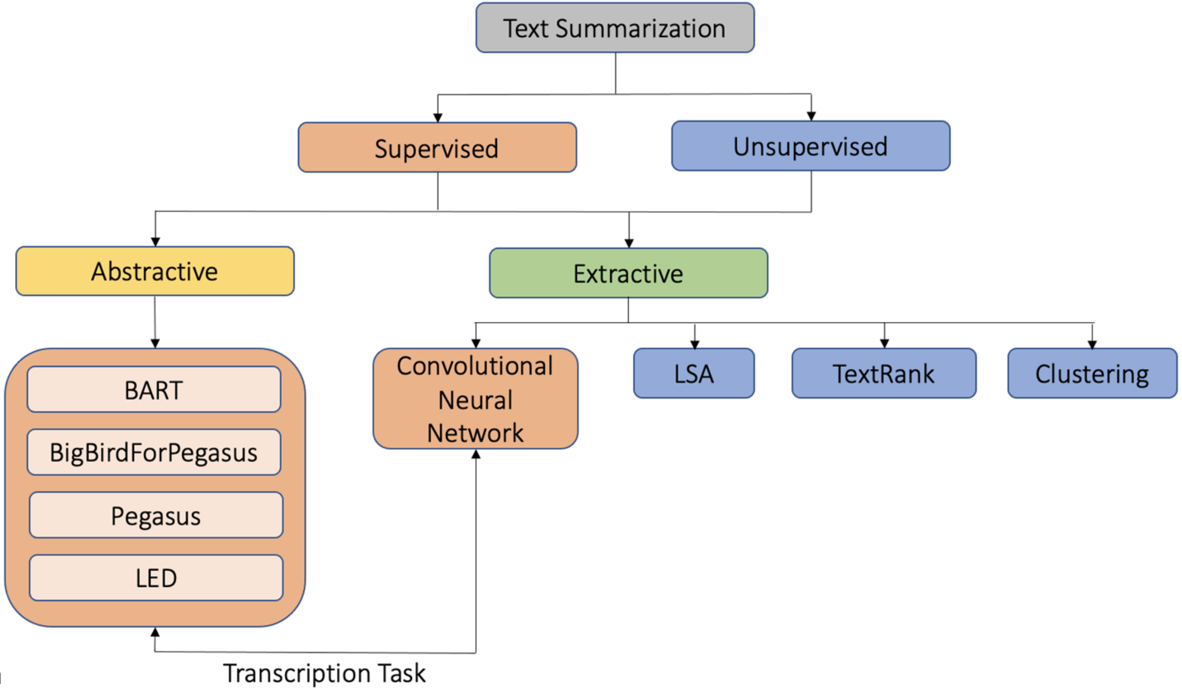
Transcription Task

- Interns are Transcribing Approximately 105 Meeting Audio Files from ATCSCC
- Each Audio File is around 10-15 minutes
- Will help with generation of speech2text models and supervised learning tasks



- Data inputs
- Preprocess
- Data transformation
- Outputs
- Model/Algorithm

Summarization Algorithms



- Supervised Algorithm
- Unsupervised Algorithm

Supervised Summarization - Abstractive

Supervised summarization is the automated process of taking a given text and condensing it to be more concise. This is a challenge when trying to identify and preserve the important information and context.

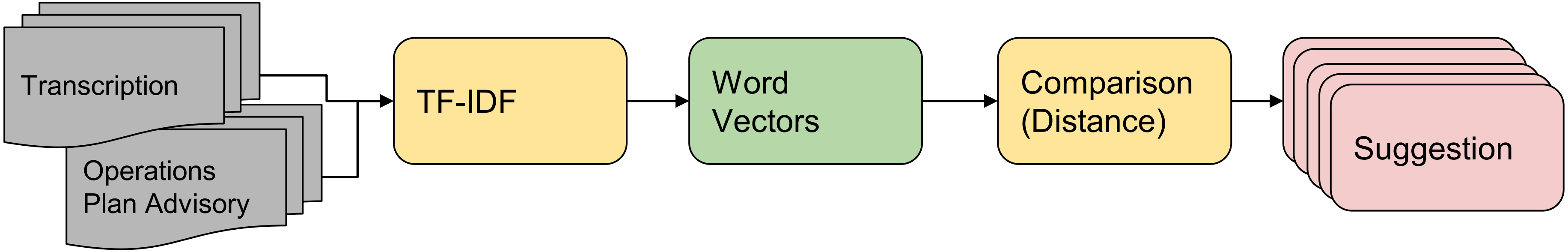
- Tested abstractive models (BART, BigBirdPegasus, LED, and Pegasus) to see if they would perform well on the transcriptions, however they did not perform well, as all F1 scores were below 0.1, which is insignificant.
- To improve results:
  - More data is needed (speech transcriptions)
  - Normalize language between speech transcription and written ops plan

Supervised Summarization - Extractive

- In contrast to abstractive summarization, extractive summarization picks out the important sentences from a passage of text, and compiles them into a summary.
- In order to train a supervised extractive model with good performance, summaries must be generated by hand
    - Important sentences are defined in the Operations Plan Advisory, but we need the corresponding sentences in the transcription
    - Can use unsupervised machine learning to shorten this process

Manual Summarization Assist Using TF-IDF

- Can use sentence similarity task to preliminarily extract important sentences
  - Since this unsupervised approach does not perform perfectly, this still needs human supervision.
- How does it work?
  - Train TF-IDF model on transcriptions AND Ops Plans.
  - Use cosine similarity distance metric to compare high-dimensional vectors, and offer user 3-5 similar sentences to choose from



Manual Summarization Assist Example

Input (From ops plan): san francisco still expecting clearing by sixteen zulu.

Output (From human transcription):

- Top 1: yeah we're going to continue on it just the weather still saying sixteen ten for the burn off we had agreed to an airborne trigger of thirty six aircraft by sixteen hundred zulu to decide and got forty five minutes to wait on that.
- **Top 2: alright down the san francisco decided to monitor the situation expected the ceilings to improve prior to sixteen zulu oakland center any thoughts from you referenced that.**
- Top 3: any other stakeholders with anything to add reference san francisco?

Future Work

- National Traffic Management Log (NTML) - data ‘in between’ meeting and operations plan advisory
  - Contains meeting notes from ATCSCC meeting
  - Sometimes referenced when creating ops plan
- Training microsoft speech studio above its current performance
- Incorporating this work into a data pipeline that can be used within operations

Questions?